9 Clustering

Import and pre-processing

In [21]:
```
import pandas as pd
import numpy as np
import scipy as sp
import plotly
import plotly.plotly as py
import plotly.figure_factory as ff
plotly.tools.set_credentials_file(username='lilcutepawz', api_key='s1zZafc0v


%matplotlib notebook
import matplotlib.pyplot as plt
import seaborn
from mpl_toolkits.mplot3d import Axes3D
plt.rcParams['font.size'] = 14
from sklearn.cluster import DBSCAN
from sklearn import metrics
```

In [22]:
```
# Import data

X = pd.read_csv('../data/3D_spatial_network.txt.gz', header=None, names=['os
X = X.drop(['osm'], axis=1).sample(10000)
X.head()
```

Out[22]:

	lat	lon	alt
115954	9.914291	57.066334	1.075407
37636	8.899517	56.757708	11.193969
337386	9.964541	57.275934	38.956355
113565	10.424281	57.436673	27.396978
256465	9.896475	57.070760	3.111426

In [23]:
```
# Transform data

XX = X.copy()
XX['alt'] = (X.alt - X.alt.mean())/X.alt.std()
XX['lat'] = (X.lat - X.lat.mean())/X.lat.std()
XX['lon'] = (X.lon - X.lon.mean())/X.lon.std()

XX.head()
```

Out[23]:

	lat	lon	alt
115954	0.308535	-0.065197	-1.132141
37636	-1.295042	-1.129805	-0.592666
337386	0.387940	0.657821	0.887495
113565	1.114435	1.212294	0.271203
256465	0.280380	-0.049928	-1.023590

1. DBSCAN

a. Using DBSCAN iterate (for-loop) through different values of `min_samples` (1 to 10) to find clusters in the road-data used in the Lesson

In [24]:
```
dbscan = DBSCAN(eps=0.5, min_samples=1)
XX.cluster = dbscan.fit_predict(XX[['lat','lon', 'alt']])
# cluster_dict = {'min_sample': min_sample, 'clusters': len(XX.cluster.value
# print(min_sample, cluster_dict)
# clusters.append(cluster_dict)
```

In [26]:
```
# # Establish variables, list in for loop

min_samples = range(1,11)
# # list(min_sample)

clusters = []
# min_sample_scores = []

# for loop to run model

for min_sample in min_samples:

    dbscan = DBSCAN(eps=0.05, min_samples=min_sample)
    XX['cluster'] = dbscan.fit_predict(XX[['lat','lon', 'alt']])
    cluster_dict = {'min_sample': min_sample, 'clusters': len(XX['cluster'].
    print(min_sample, cluster_dict)
    clusters.append(cluster_dict)
```

...

In [149]:
```
clusters
```

Out[149]:
```
[{'clusters': 4731, 'min_sample': 1},
 {'clusters': 1317, 'min_sample': 2},
 {'clusters': 619, 'min_sample': 3},
 {'clusters': 345, 'min_sample': 4},
 {'clusters': 229, 'min_sample': 5},
 {'clusters': 135, 'min_sample': 6},
 {'clusters': 110, 'min_sample': 7},
 {'clusters': 90, 'min_sample': 8},
 {'clusters': 62, 'min_sample': 9},
 {'clusters': 49, 'min_sample': 10}]
```

In [151]:
```
clusters_sample = pd.DataFrame(clusters)
clusters_sample.head()
```

Out[151]:

	clusters	min_sample
0	4731	1
1	1317	2
2	619	3
3	345	4
4	229	5

b. and calculate the Silohouette Coeff for `min_samples`.

In [134]:
```
for min_sample in min_samples:

    dbscan = DBSCAN(eps=0.4, min_samples=min_sample)
    XX['cluster'] = dbscan.fit_predict(XX[['lat','lon', 'alt']])
#     clusters.append(XX['cluster'])
    score = metrics.silhouette_score(XX[['lon','lat','alt']], XX['cluster'])
    print(min_sample, score)
    min_sample_score = {'min_sample': min_sample, 'score': score}
    min_sample_scores.append(min_sample_score)
```

```
1 -0.16595282393
2 -0.0745333011383
3 -0.0200024531798
4 0.095012015895
5 0.139377888269
6 0.133918279376
7 0.135890346625
8 0.135890346625
9 0.133162531791
10 0.13049762749
```

In [154]:
```
df_sample = pd.DataFrame(min_sample_scores)
df_sample.head()
```

Out[154]:

	min_sample	score
0	1	-0.026420
1	2	-0.026420
2	3	-0.026420
3	4	0.132232
4	5	0.154515

In [155]:
```
df_sample['clusters'] = clusters_sample['clusters']
df_sample.head()
```

Out[155]:

	min_sample	score	clusters
0	1	-0.026420	4731.0
1	2	-0.026420	1317.0
2	3	-0.026420	619.0
3	4	0.132232	345.0
4	5	0.154515	229.0

c. and `epsilon` (.05 to .5, in steps of .01) to find clusters in the road-data used in the Lesson

In [144]:
```
epsilons = np.arange(0.05, 0.51, 0.01)
# list(epsilon)[:5]

clusters = []
# min_sample_scores = []

# for loop to run model

for epsilon in epsilons:

    dbscan = DBSCAN(eps=epsilon)
    XX.cluster = dbscan.fit_predict(XX[['lat','lon', 'alt']])
    cluster_dict = {'epsilon': epsilon, 'clusters': len(XX.cluster.value_cou
    print(epsilon, cluster_dict)
    clusters.append(cluster_dict)
```

```
0.05 {'epsilon': 0.050000000000000003, 'clusters': 229}
0.06 {'epsilon': 0.060000000000000005, 'clusters': 242}
0.07 {'epsilon': 0.070000000000000007, 'clusters': 259}
0.08 {'epsilon': 0.080000000000000016, 'clusters': 271}
0.09 {'epsilon': 0.090000000000000011, 'clusters': 277}
0.1 {'epsilon': 0.10000000000000001, 'clusters': 255}
0.11 {'epsilon': 0.11000000000000001, 'clusters': 217}
0.12 {'epsilon': 0.12000000000000001, 'clusters': 149}
0.13 {'epsilon': 0.13, 'clusters': 98}
0.14 {'epsilon': 0.14000000000000001, 'clusters': 80}
0.15 {'epsilon': 0.15000000000000002, 'clusters': 59}
0.16 {'epsilon': 0.16000000000000003, 'clusters': 43}
0.17 {'epsilon': 0.17000000000000004, 'clusters': 35}
0.18 {'epsilon': 0.18000000000000005, 'clusters': 26}
0.19 {'epsilon': 0.19, 'clusters': 20}
0.2 {'epsilon': 0.20000000000000001, 'clusters': 14}
0.21 {'epsilon': 0.21000000000000002, 'clusters': 11}
0.22 {'epsilon': 0.22000000000000003, 'clusters': 11}
0.23 {'epsilon': 0.23000000000000004, 'clusters': 8}
```

In [145]:
```
clusters_eps = pd.DataFrame(clusters)
clusters_eps.head()
```

Out[145]:

	clusters	epsilon
0	229	0.05
1	242	0.06
2	259	0.07
3	271	0.08
4	277	0.09

d. and calculate the Silohouette Coeff for `epsilon`.

In [141]:
```
epsilon_scores = []

for epsilon in epsilons:

    dbscan = DBSCAN(eps=epsilon)
    labels = dbscan.fit_predict(XX[['lat','lon', 'alt']])
    score = metrics.silhouette_score(XX[['lon','lat','alt']], labels)
    print(epsilon, score)
    epsilon_score = {'epsilon': epsilon, 'score': score}
    epsilon_scores.append(epsilon_score)
```

```
0.05 -0.419523918386
0.06 -0.342683583237
0.07 -0.338527485292
0.08 -0.311017304843
0.09 -0.261419155027
0.1 -0.227767298122
0.11 -0.267681514048
0.12 -0.391305145549
0.13 -0.531491548534
0.14 -0.526259239323
0.15 -0.478197542066
0.16 -0.470136171451
0.17 -0.479690948103
0.18 -0.473927789749
0.19 -0.466245223068
0.2 -0.426051587094
0.21 -0.366362047219
0.22 -0.364457852255
0.23 -0.26992793341
```

In [230]:
```
df_eps = pd.DataFrame(epsilon_scores)
df_eps.head()
```

Out[230]:

	epsilon	score
0	0.05	-0.419524
1	0.06	-0.342684
2	0.07	-0.338527
3	0.08	-0.311017
4	0.09	-0.261419

In [153]:
```
df_eps['clusters'] = clusters_eps['clusters']
df_eps.head()
```

Out[153]:

	epsilon	score	clusters
0	0.05	-0.413108	229
1	0.06	-0.332175	242
2	0.07	-0.305814	259
3	0.08	-0.259021	271
4	0.09	-0.255028	277

e. Plot *one* line plot with the multiple lines generated from the min_samples and epsilon values.

In [160]:
```
df_eps.shape, df_sample.shape
```

Out[160]: ((46, 3), (34, 3))

In [166]:
```
df_sample.head()
```

Out[166]:

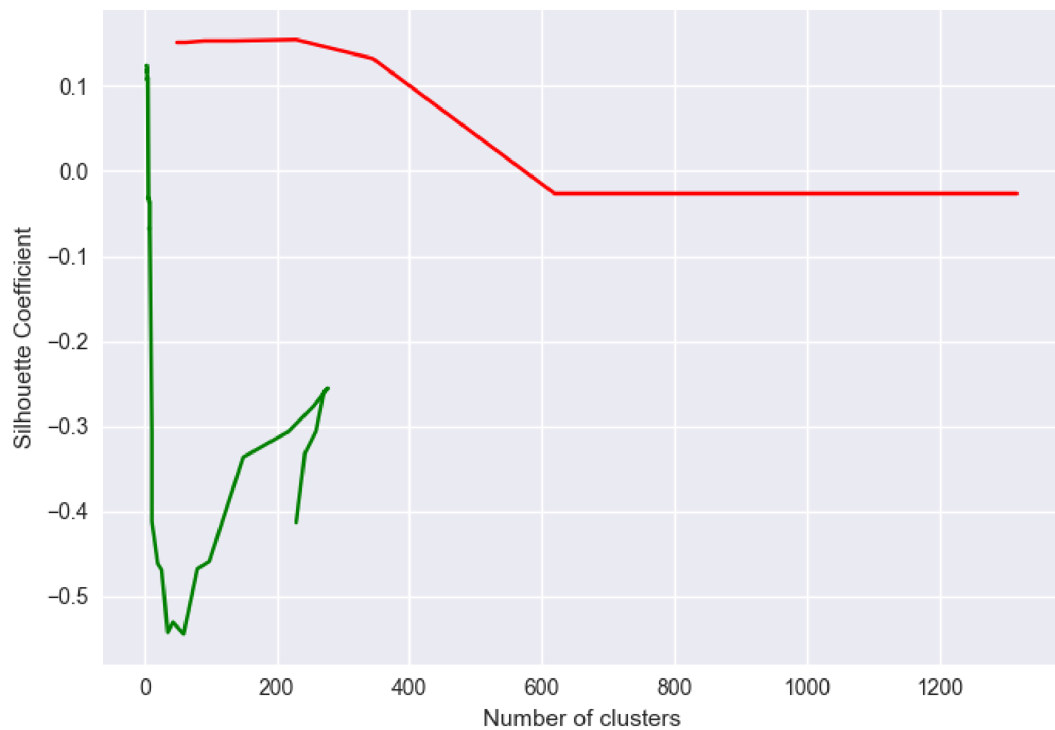
	min_sample	score	clusters
0	1	-0.026420	4731.0
1	2	-0.026420	1317.0
2	3	-0.026420	619.0
3	4	0.132232	345.0
4	5	0.154515	229.0

In [171]:
```
df_sample_plot = df_sample[1:]
df_sample_plot.head()
```

Out[171]:

	min_sample	score	clusters
1	2	-0.026420	1317.0
2	3	-0.026420	619.0
3	4	0.132232	345.0
4	5	0.154515	229.0
5	6	0.153127	135.0

In [178]:
```
# plot the results
plt.figure()
plt.plot(df_eps_plot['clusters'], df_eps_plot['score'], color='g')
plt.plot(df_sample_plot['clusters'], df_sample_plot['score'], color='r')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.show()
```



f. Use a 2D array to store the SilCoeff values, one dimension represents `min_samples`, the other represents epsilon.

In [261]:
```
from tqdm import tqdm_notebook as tqdm
```

In [262]:
```
# min_samples = range(1,11)
# epsilons = np.arange(0.05, 0.51, 0.01)

# fast for debug
min_samples = range(1,11, 2)
epsilons = np.arange(0.2, 0.51, 0.1)

silcoeff = np.zeros([len(min_samples), len(epsilons)])

for i, min_sample in enumerate(tqdm(min_samples, desc='min_samples')):
    for j, epsilon in enumerate(tqdm(epsilons, desc='epsilons')):


        dbscan = DBSCAN(eps=epsilon, min_samples=min_sample)
        labels = dbscan.fit_predict(XX[['lat','lon', 'alt']])
        silcoeff[i,j] = metrics.silhouette_score(XX[['lon','lat','alt']], la
```

In [256]:
```
# silcoeff[0,0] = np.nan
```

In [265]:
```
list(silcoeff)
```

Out[265]:
```
[array([-0.57886386, -0.28390485, -0.16595282, -0.02641958]),
 array([-0.46056487, -0.14476693, -0.02000245, -0.02641958]),
 array([-0.42605159, -0.14603055,  0.13937789,  0.15451542]),
 array([-0.35454116, -0.02232658,  0.13589035,  0.15312689]),
 array([-0.36447705,  0.01737273,  0.13316253,  0.15131648])]
```

In [ ]:
```
len(min_samples)
```

In [283]:
```
df_eps_short_scores = df_eps['score'][:34]
# df_eps_short_scores.shape

df_eps['min_score'] = df_eps['score'][:34]
df_eps.head()

df_silcoeffs = df_eps.groupby('epsilon')['min_score','score'].apply(list).to
df_silcoeffs
```

In [8]:
```
import plotly.figure_factory as ff

# df_eps

df_eps_ff = ff.create_table(df_eps)
df_eps_ff = py.iplot(df_eps_ff, filename='table1')
df_eps_ff
```

...

In [337]:
```
# for s in silcoeffs:

#     for eps_silc in eps_silcs:
#         silcoeff.append([df_eps['score']])
#         print(silcoeff)
#     for sample_silc in sample_silcs:
#         silcoeff.append([df_sample['score']])
#     print(silcoeff)

# establish variables, shorten computation time
min_samples = range(1,11, 1)
epsilons = np.arange(0.2, 0.51, 0.1)

# create empty dictionary
silcovfefe = np.zeros([len(min_samples), len(epsilons)])
silcovfefe.shape

# for loop, iterate through i,j
for i,min_sample in enumerate(min_samples):
    for j, epsilon in enumerate(epsilons):

        dbscan = DBSCAN(eps=epsilon, min_samples=min_sample)
        labels = dbscan.fit_predict(XX[['lat','lon', 'alt']])
#         append silhouette coefficient of i,j to empty dictionary
        silcovfefe[i,j] = metrics.silhouette_score(XX[['lon','lat','alt']],

print(silcovfefe)
```

```
[[-0.57886386 -0.28390485 -0.16595282 -0.02641958]
 [-0.50891917 -0.16142834 -0.0745333  -0.02641958]
 [-0.46056487 -0.14476693 -0.02000245 -0.02641958]
 [-0.42684482 -0.14596664  0.09501202  0.13223161]
 [-0.42605159 -0.14603055  0.13937789  0.15451542]
 [-0.38925167  0.01322098  0.13391828  0.15312689]
 [-0.35454116 -0.02232658  0.13589035  0.15312689]
 [-0.34056536  0.00671813  0.13589035  0.15312689]
 [-0.36447705  0.01737273  0.13316253  0.15131648]
 [-0.3163645  -0.02514957  0.13049763  0.15131648]]
```

In [338]:
```
len(min_samples), len(epsilons)
```

Out[338]: (10, 4)

2D Array of Silhouettes: min_samples + epsilons

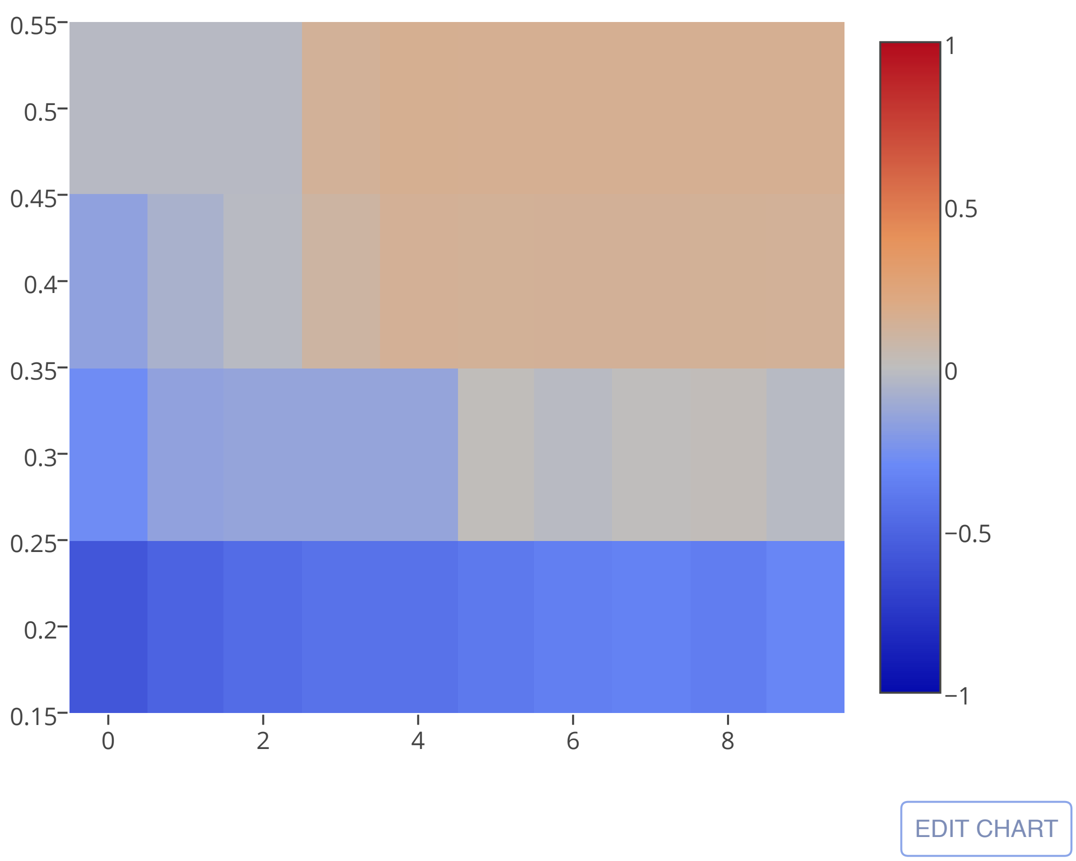
In [340]:
```
silcovfefe_t = np.array(silcovfefe)
silcovfefe_t = silcovfefe_t.transpose()
silcovfefe_t
```

Out[340]:
```
array([[-0.57886386, -0.50891917, -0.46056487, -0.42684482, -0.42605159,
        -0.38925167, -0.35454116, -0.34056536, -0.36447705, -0.3163645 ],
       [-0.28390485, -0.16142834, -0.14476693, -0.14596664, -0.14603055,
         0.01322098, -0.02232658,  0.00671813,  0.01737273, -0.02514957],
       [-0.16595282, -0.0745333 , -0.02000245,  0.09501202,  0.13937789,
         0.13391828,  0.13589035,  0.13589035,  0.13316253,  0.13049763],
       [-0.02641958, -0.02641958, -0.02641958,  0.13223161,  0.15451542,
         0.15312689,  0.15312689,  0.15312689,  0.15131648,  0.1513164
8]])
```

In [4]:
```
# heatmap for silcovfefe
import plotly.graph_objs as go
```

In [359]:
```
silcovfefe_heatmap = go.Heatmap(z=silcovfefe_t, y=epsilons, zmax=1, zmin=-1)
data=[silcovfefe_heatmap]
layout = go.Layout(
    title='Silhouette coefficients'
)

fig = go.Figure(data=data, layout=layout)
py.iplot(data, filename='silcovfefe-heatmap')
```

Out[359]:



Still figuring out how to use plotly. Heatmap of the 2D array silhouette coefficients. As you can see, bright red would be phenomenal but is nowhere on the map. The silhouette coefficient appears to improve as both the minimum number of samples and epsilons increase.

2. Clustering your own data

Using your own data, find relevant clusters/groups within your data. If your data is labeled already, with a class that you are attempting to predict, be sure to not use it in fitting/training/predicting.

You may use the labels to compare with predictions to show how well the clustering performed using one of the clustering metrics (http://scikit-learn.org/stable/modules/clustering.html#clustering-performance-evaluation (http://scikit-learn.org/stable/modules/clustering.html#clustering-performance-evaluation)).

If you don't have labels, use the silhouette coefficient to show performance. Find the optimal fit for your data but you don't need to be as exhaustive as above.

Additionally, show the clusters in 2D and 3D plots.

For bonus, try using PCA first to condense your data from N columns to less than N.

Two items are expected:

- Metric Evaluation Plot
- Plots of the clustered data

Note

You may use any for both parts 1 and 2, I only recommend using the data I used in the Lesson for part 1. I've included several new datasets in the `data/` folder, such as `beers.csv`, `snow_tweets.csv`, `data/USCensus1990.data.txt.gz`. You do not need to unzip or ungzip any data files. Pandas can open these files on its own.

In [40]:
```
import pandas as pd
import numpy as np
import scipy as sp
import plotly
import plotly.plotly as py
import plotly.figure_factory as ff
plotly.tools.set_credentials_file(username='lilcutepawz', api_key='s1zZafc0v


%matplotlib notebook
import matplotlib.pyplot as plt
import seaborn
from mpl_toolkits.mplot3d import Axes3D
plt.rcParams['font.size'] = 14
from sklearn.cluster import DBSCAN
from sklearn import metrics
```

Data: Beer.csv

abv: alcohol by volume - ibu: hops measurement units

In [61]:
```
# Import data
X = pd.read_csv('../data/beers.csv', header=0, index_col=0)

X.head()
```

Out[61]:

	abv	ibu	id	name	style	brewery_id	ounces
0	0.050	NaN	1436	Pub Beer	American Pale Lager	408	12.0
1	0.066	NaN	2265	Devil's Cup	American Pale Ale (APA)	177	12.0
2	0.071	NaN	2264	Rise of the Phoenix	American IPA	177	12.0
3	0.090	NaN	2263	Sinister	American Double / Imperial IPA	177	12.0
4	0.075	NaN	2262	Sex and Candy	American IPA	177	12.0

In [63]:
```
X['ibu'].isnull().value_counts()
```

Out[63]:
```
False    1405
True     1005
Name: ibu, dtype: int64
```

In [68]:
```
X.shape
```

Out[68]: (2410, 7)

In [72]:
```
# X = X.fillna(0)
# X.head()

# dropna values
X = X.dropna(axis=0, how='any')

X.shape
```

Out[72]: (1403, 7)

In [73]:
```
X.head()
```

Out[73]:

	abv	ibu	id	name	style	brewery_id	ounces
14	0.061	60.0	1979	Bitter Bitch	American Pale Ale (APA)	177	12.0
21	0.099	92.0	1036	Lower De Boom	American Barleywine	368	8.4
22	0.079	45.0	1024	Fireside Chat	Winter Warmer	368	12.0
24	0.044	42.0	876	Bitter American	American Pale Ale (APA)	368	12.0
25	0.049	17.0	802	Hell or High Watermelon Wheat (2009)	Fruit / Vegetable Beer	368	12.0

Find relevant clusters/groups within your data.

In [75]:
```
X = pd.get_dummies(X)
X.head()
```

Out[75]:

	abv	ibu	id	brewery_id	ounces	name_#002 American I.P.A.	name_#004 Session I.P.A.	name_#9	name_077XX	name_
14	0.061	60.0	1979	177	12.0	0	0	0	0	
21	0.099	92.0	1036	368	8.4	0	0	0	0	
22	0.079	45.0	1024	368	12.0	0	0	0	0	
24	0.044	42.0	876	368	12.0	0	0	0	0	
25	0.049	17.0	802	368	12.0	0	0	0	0	

5 rows × 1421 columns

In [76]:
```
# K-means with N clusters
N = 7
from sklearn.cluster import KMeans
km = KMeans(n_clusters=N, random_state=1)
km.fit(X)
```

Out[76]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=7, n_init=10, n_jobs=1, precompute_distances='auto',
    random_state=1, tol=0.0001, verbose=0)
```

In [77]:
```
set(km.labels_)
```

Out[77]:
```
{0, 1, 2, 3, 4, 5, 6}
```

In [78]:
```
X['cluster'] = km.predict(X)

X.cluster.value_counts()
```

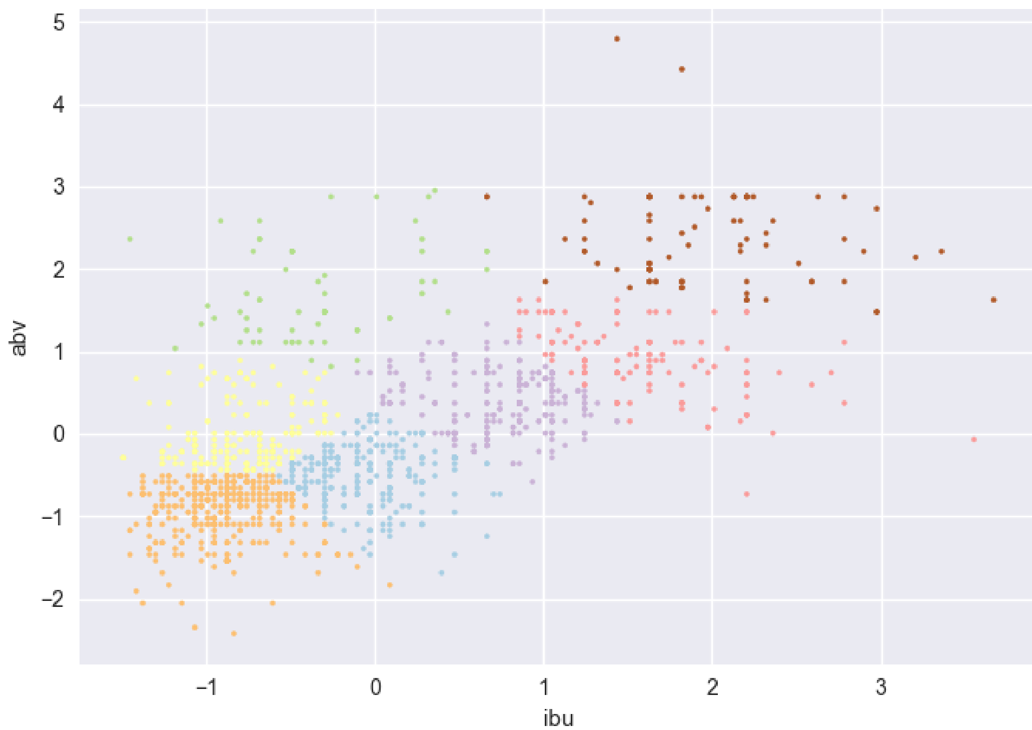
Out[78]:
```
4    243
2    238
6    221
3    203
1    203
0    195
5    100
Name: cluster, dtype: int64
```

In [82]:
```
fig = plt.figure()
plt.scatter(X.abv, X.ibu, c=X.cluster, s=5, cmap='Paired')

plt.xlabel('abv')
plt.ylabel('ibu')
plt.show()
```

In [83]:
```
XX = X.copy()
XX['ibu'] = (X.ibu - X.ibu.mean())/X.ibu.std()
XX['abv'] = (X.abv - X.abv.mean())/X.abv.std()
```

In [84]:
```
# Rerun model with normalized data
km = KMeans(n_clusters=N, random_state=1)
XX['cluster'] = km.fit_predict(XX[['ibu', 'abv']])
```

In [86]:
```
fig = plt.figure()
plt.scatter(XX.ibu, XX.abv, c=XX.cluster, s=5, cmap='Paired')

plt.xlabel('ibu')
plt.ylabel('abv')
plt.show()
```

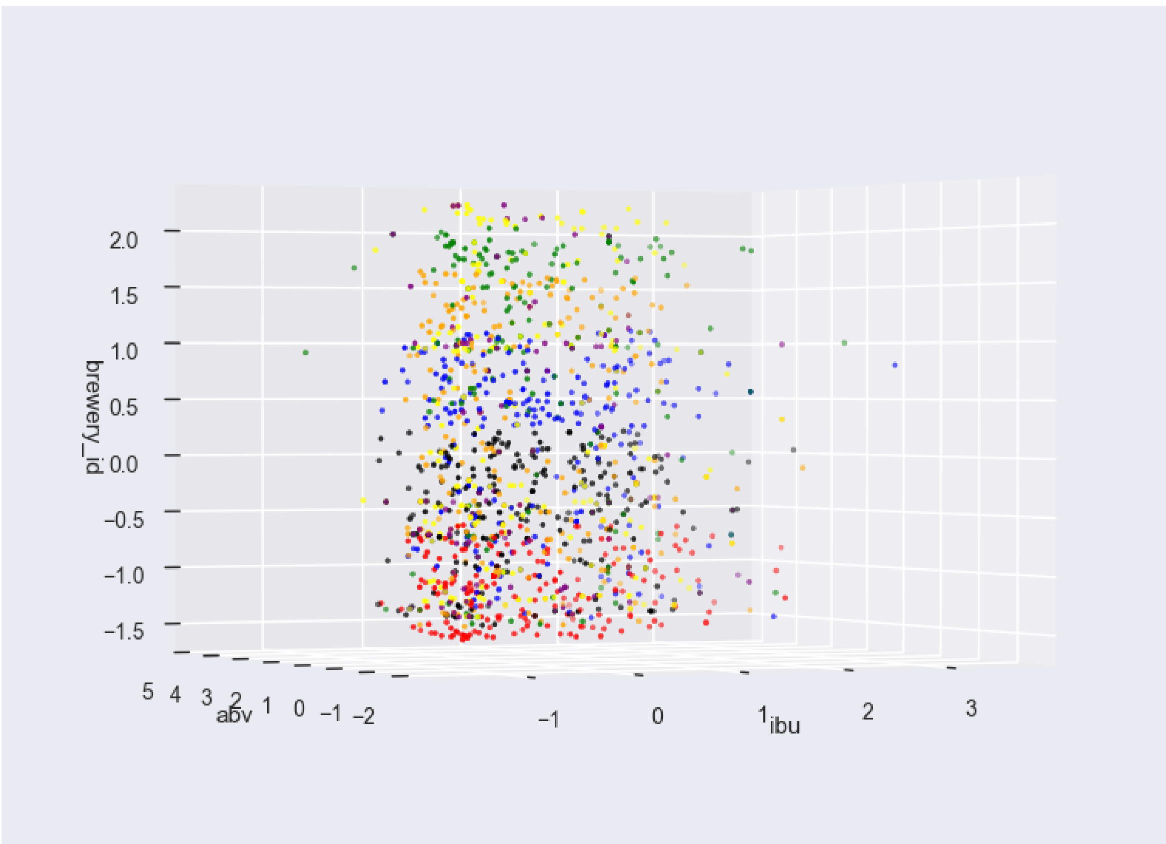


In [105]:
```
XX = X.copy()
XX['ibu'] = (X.ibu - X.ibu.mean())/X.ibu.std()
XX['abv'] = (X.abv - X.abv.mean())/X.abv.std()
XX['brewery_id'] = (X.brewery_id - X.brewery_id.mean())/X.brewery_id.std()
# XX['ounces'] = (X.ounces - X.ounces.mean())/X.ounces.std()
```

In [106]:
```
XX.cluster.value_counts()
```

Out[106]:
```
4    243
2    238
6    221
3    203
1    203
0    195
5    100
Name: cluster, dtype: int64
```

In [109]:
```
# create a "colors" array for plotting
import numpy as np
colors = np.array(['red', 'green', 'blue', 'yellow', 'orange', 'purple', 'bl

fig = plt.figure()
plt.clf()
ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=48, azim=140)

plt.cla()

ax.scatter(XX['ibu'], XX['abv'], XX['brewery_id'], c=colors[XX.cluster], s=5

ax.set_xlabel('ibu')
ax.set_ylabel('abv')
ax.set_zlabel('brewery_id')

plt.show()
# ax.scatter(XX['ibu'], XX['abv'], XX['ounces'], c=colors[XX.cluster], s=5)

# ax.set_xlabel('ibu')
# ax.set_ylabel('abv')
# ax.set_zlabel('ounces')
# plt.show()
```




```
/Users/katie/anaconda3/envs/py36/lib/python3.6/site-packages/matplotlib/a
xes/_axes.py:545: UserWarning:

No labelled objects found. Use label='...' kwarg on individual plots.
```

In [97]:
```
# calculate SC for K=7
from sklearn import metrics
metrics.silhouette_score(XX[['ibu', 'abv', 'brewery_id']], XX.cluster)
```

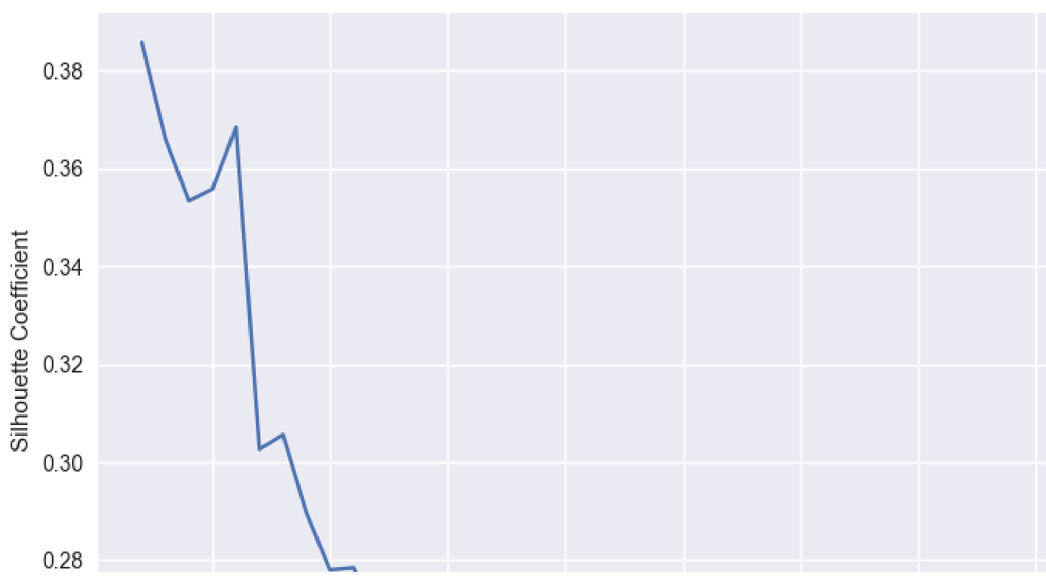
Out[97]: -0.062820373307451327

In [99]:
```
# calculate SC for K=2 through K=19
k_range = range(2, 40)
scores = []

for k in k_range:
    km = KMeans(n_clusters=k, random_state=1)
    labels = km.fit_predict(XX[['ibu', 'abv', 'brewery_id']])
    scores.append(metrics.silhouette_score(XX[['ibu', 'abv', 'brewery_id']],
```

In [110]:
```
scores[:5]
```

Out[110]:
```
[0.3857409610342693,
 0.36606781700505159,
 0.35337054181303373,
 0.3558033430441358,
 0.36844448692563658]
```

In [111]:
```
# plot the results
plt.figure()
plt.plot(k_range, scores)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
plt.show()
```



The clusters are quite distinct when plotting normalized data of alcohol by volume and international bitterness units. The model performs better generally with a lower number of clusters. It peaks at 6, and then again

around 2-3 clusters. That said, a silhouette score around 0.4 isn't bad but also isn't great. I also removed all rows that contained nan values, but this also eliminated about 30-40% of the records. Perhaps imputing some of the data may provide improved results.

PCA - still work in progress

In [132]:
```
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

iris = datasets.load_iris()

# Import data
X = pd.read_csv('../data/beers.csv', header=0, index_col=0)

X.head()
```

Out[132]:

	abv	ibu	id	name	style	brewery_id	ounces
0	0.050	NaN	1436	Pub Beer	American Pale Lager	408	12.0
1	0.066	NaN	2265	Devil's Cup	American Pale Ale (APA)	177	12.0
2	0.071	NaN	2264	Rise of the Phoenix	American IPA	177	12.0
3	0.090	NaN	2263	Sinister	American Double / Imperial IPA	177	12.0
4	0.075	NaN	2262	Sex and Candy	American IPA	177	12.0

In [133]:
```
# dropna values
X = X.dropna(axis=0, how='any')

X.shape
```

Out[133]: (1403, 7)

In [134]:
```
X['style_num'] = X['style'].astype('category').cat.codes

X.head()
```

Out[134]:

	abv	ibu	id	name	style	brewery_id	ounces	style_num
14	0.061	60.0	1979	Bitter Bitch	American Pale Ale (APA)	177	12.0	15
21	0.099	92.0	1036	Lower De Boom	American Barleywine	368	8.4	5
22	0.079	45.0	1024	Fireside Chat	Winter Warmer	368	12.0	88
24	0.044	42.0	876	Bitter American	American Pale Ale (APA)	368	12.0	15
25	0.049	17.0	802	Hell or High Watermelon Wheat (2009)	Fruit / Vegetable Beer	368	12.0	55

In [135]:
```
X['style_num'].value_counts()[:5]
```

Out[135]:
```
13    301
15    153
3      77
10     75
17     61
Name: style_num, dtype: int64
```

In [142]:
```
XX = X.drop('style', 1)
XX = XX.drop('style_num', 1)
XX = XX.drop('id', 1)
XX = XX.drop('name', 1)
XX.head()
```

Out[142]:

	abv	ibu	brewery_id	ounces
14	0.061	60.0	177	12.0
21	0.099	92.0	368	8.4
22	0.079	45.0	368	12.0
24	0.044	42.0	368	12.0
25	0.049	17.0	368	12.0

In [143]:
```
print(type(XX))
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [144]:
```
type(XX.values)
```

Out[144]:
```
numpy.ndarray
```

In [145]:
```
XX = XX.values
y = X['style_num']
target_names = X['style']
```

In [1]:
```
target = X['style_num']
np.array(target)
type(target)
```

...

In [ ]:
```
```